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LOVE, HATE AND MURDER:
COMMITMENT DEVICES IN VIOLENT RELATIONSHIPS

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ABSTRACT

Many violent relationships are characterized by a high degree of cyclicality: women who are the victims of domestic violence often leave and return multiple times. To explain this we develop a model of time inconsistent preferences in the context of domestic violence. This time inconsistency generates a demand for commitment. We present supporting evidence that women in violent relationships display time inconsistent preferences by examining their demand for commitment devices. We find that "no-drop" policies -- which compel the prosecutor to continue with prosecution even if the victim expresses a desire to drop the charges -- result in an increase in reporting. No-drop policies also result in a decrease in the number of men murdered by intimates suggesting that some women in violent relationships move away from an extreme type of commitment device when a less costly one is offered.

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1. Introduction

Everyday roughly 14 thousand women in the US are battered and 4 are killed by their intimate partners. An interesting and often puzzling aspect of violent relationships is its cyclical nature (Walker, 1979; Strube, 1988). Battered women who leave and seek the help of authorities in pressing criminal charges against their partners often return to the abuser and ask the authorities to drop the charges, despite the high probability of future victimization. The well-documented fact that women repeatedly change their mind after leaving or reporting the batterer suggests that the idea of a rational agent with stable preferences weighing the benefits and costs of reporting abuse and leaving may not be an appropriate framework for studying domestic violence. Rather, a framework in which preferences change with battering may be more appropriate.

In this paper we propose a model of time inconsistent preferences to study domestic violence. The victim's preferences change with time from the battering incident. That is, right after a battering incident, while in shock and fear, a woman's valuation of the relationship is low but increases as time passes. This is consistent with empirical evidence on how emotional states affect the desirability of different goods or actions (see Loewenstein, 1996; Read and van Leeuwen, 1998; Loewenstein et al, 2001; Gilbert et al. 2002; Wilson and Gilbert 2003). This model can explain how a woman might leave her partner after a battering incident with the intention of not returning, but after some time, her emotional attachment resurfaces and she returns.

In principle, models with changing but time consistent preferences (ie: traditional models of rational addiction or the cue theory of consumption) can also explain cyclical behavior.[2] However, the key difference between time consistent and inconsistent agents is that the latter, if aware, will try to discipline their future behavior by committing themselves to a certain future action. In the case of smoking, for example, a person may wish to commit him or herself to quitting and therefore may welcome devices such as higher taxes (Gruber and Koszegi, 2001; Gruber and Mullanaithan, 2002). In the case of domestic violence, a woman may want to commit herself not to return to the batterer and thus welcome policies that commit her to doing so.

In this paper we study the demand for such a commitment device: "no-drop" policy of prosecution. This policy stipulates that once a woman brings charges against a batterer, the prosecution will continue regardless of her stated wishes to drop the charges. In this way, no-drop policies offer a commitment device for women who want to terminate a violent relationship but fear that their intentions may change.

We develop a model of time inconsistent preferences in the context of violent relationships that yields two predictions. First, if women are sufficiently time inconsistent, no-drop policies will increase reporting of battering incidents. That is, women will be more likely to report violent partners when they are offered a device that will enable them to commit to prosecuting them. Second, no-drop policies will reduce the number of men murdered by intimates as women in violent relationships will substitute an expensive private commitment device (murder of the batterer) for a cheaper public commitment device provided by the no-drop policy.

We follow this with empirical estimation of the impact of no drop policies on reporting and intentional intimate partner homicide. The results provide evidence in favor

[2] For consumption cycles in rational addiction models see Ryder and Heal (1973), Becker and Murphy (1988), Dockner and Feichtinger (1993) and Palacios-Huerta (2003). For the cue theory of consumption, which can also provide cycles, see Laibson (2001).

of our theory of time inconsistent preferences in battering relationships. First, we find that no-drop policies lead to a 14-18 percent increase in reporting, as measured by the number of men arrested for domestic violence. This is consistent with the model's prediction that women in battering relationships demand commitment devices if they are sufficiently time inconsistent. We also find that no-drop policies led to a 15-22 percent decline in the number of *men* intentionally murdered by intimates, a large fraction of whom have documented histories of battering. Our finding that no-drop policies reduce the number of men murdered by intimates provides evidence that battered women will move away from an extreme type of commitment device –murder– when a less costly one is offered in the form of no-drop prosecution. Finally, we find no evidence that no drop policies lead to a reduction in domestic violence as measured by the number of women killed by intimate partners or the number of women admitted to the hospital for an assault. This suggests that the reduction in the number of men being murdered by intimates can not be explained by a reduction in the number of violent relationships due to no-drop policies. Nor do we believe that the reduction can be due to underlying changes in the type or composition of violent relationships as the effect appears to be immediate.

The contribution of this paper is twofold. First, we explain the cyclical nature of battering relationships in the context of time inconsistent preferences. Though an economist (Mill, 1869) was one of the first to address the issue of domestic violence, modern economic literature on the subject is somewhat limited. The recent literature has focused on explaining violence under the assumption of time consistent rational agents and consists of a handful of studies.[3] The main distinction between our work and previous work is our assumption of time inconsistent agents.

There exists an extensive literature on time inconsistency of time-preferences that can trace its roots to Strotz (1956) and Phelps and Pollak (1968). Yet most of the literature has focused on present biased preferences as in Ainslie (1991), Loewenstein and Prelec (1992), Laibson (1997) and O'Donoghue and Rabin (1999) among others. Our model differs in that the time inconsistency of preference is not in regards to discounting but in regards to the valuation of possible choices in a given period.

Our second contribution is that we provide new empirical evidence consistent with the theory of time inconsistent preferences, adding to the growing non-experimental empirical evidence of time inconsistency and the demand for commitments, see Angeletos et al. (2001), Madrian and Shea (2001), Gruber and Mullainathan (2002) and Della Vigna and Malmendier (2003).

The fact that the introduction of no-drop policies reduces the number of men murdered by intimates has interesting implications outside domestic violence. It implies that when agents are time inconsistent, the analysis of policies that incorporate a commitment element should consider the effect on the demand for alternative

[3] Tauchen et al (1991) provide a non-cooperative model of families that incorporates the possibility of violence and study the impact of future changes in male and female incomes among 125 women in a battered women's shelter in Santa Barbara. Aizer (2006) estimates the impact of the shrinking male-female wage gap on violence against women and the impact of domestic violence on birth outcomes. Regarding the effect of policies, Tauchen and Witte (1995) study the impact of different arrest policies on future violence. Dee (2003) and Stevenson and Wolfers (2006) estimate the impact of unilateral divorces laws on intimate partner homicide and suicide. Iyengar (2007) estimates the impact of mandatory arrests on intimate partner homicide. Finally, Farmer and Tiefenthaler (1996) provide a signaling model of leaving a violent relationship and Pollak (2002) presents a model of intergenerational transmission of domestic violence.

commitment devices. In this case, a public policy that offers a cheap commitment device results in a decrease in the demand for a costly private commitment device.

The rest of this paper is laid out as follows. In section 2 we provide background information on the prevalence and costs of domestic violence in the US. In section 3 we describe the cyclical nature of battering. In section 4 we describe no-drop policies and present anecdotal evidence in favor of the idea of time inconsistent preferences. In section 5 we present a model of domestic violence with time inconsistent preferences and study the effect of no-drop policies on violence and reporting. In section 6 we present our empirical estimates of the impact of no drop policies on domestic violence, reporting (as measured by arrest rates) and intimate partner homicide.

2. The problem of battering

Domestic violence is a problem of considerable social importance in the US given its prevalence and the severity of its impact on the health and well-being of those affected. In 2001, women in the US reported 590 thousand incidents of rape, sexual and other assault at the hands of intimate partners and on average 4 women are killed each day by a partner. Though the number of reported assaults is high – it is likely an underestimate. Survey data suggest that only one half to one fifth of such assaults are reported to the police.[4] Data gathered through personal surveys and medical professional assessments suggest that between 8 and 14 percent of women have been assaulted in the past year by an intimate, with lifetime prevalence estimated at 25 - 30 percent (See Jones et al. (1999). For women, intimate violence accounts for 33 percent of all homicides.

[4] Bureau of Justice Statistics (1998); 2002 Minnesota crime survey; Tjaden and Thoennes (2000b), data are from the NCVS – National Criminal Victimization Survey.

According to a report issued by the World Health Organization (WHO) in 2002, "intimate partner violence occurs in all countries, irrespective of social, economic, religious or cultural group." Findings from population-based surveys of women from 35 countries around the world suggest that between 10 and 69 percent of women have been physically assaulted by an intimate male partner at some point in their lives, with 3 to 27 percent assaulted in the last year.

The costs associated with domestic violence are significant. Women who are victims of domestic violence suffer directly both physically and emotionally from the injury itself. Reported injuries range from scratches, bruises and welts to lacerations, broken bones and head or spinal cord injuries (Tjaden and Thoennes , 2000a). One third of women injured by an intimate required medical attention and of those, 26 percent were hospitalized overnight for their injuries. The CDC estimates that the costs associated with domestic violence attributed to medical care service use amount to roughly 4 billion annually.[5]

Domestic violence also diminishes a woman's ability to work outside the home. The CDC estimates that in 1995, victims of physical assault lost on average 7.2 days of work outside the home as a direct result of their injuries and 8.4 days of household work, yielding total annual costs in terms of lost earnings in excess of $.7 billion.[6] Additional studies have found that women who had been victims of domestic violence were more

[5] Costs include both mental health and medical care costs with the latter consisting of physician visits, physical therapy, outpatient visits, inpatient care and emergency department visits. The costs were calculated using cost data from the MEPS and utilization data from the NSVAW. See CDC (2003).
[6] Costs were calculated by multiplying the estimated number of lost days by age group by the average earnings of women in that age group and summing over all age groups. The costs reflect 1995 earnings and incidence rates.

likely to use welfare, have longer unemployment spells, and experience higher job turnover than those who had not (Lloyd and Taluc, 1999; Browne et al., 1999).

The children of women abused by their partners also suffer. Parker et al. (1994) study 1200 births to women in Boston and find that women who were the victims of intimate violence were at significant risk for low-birthweight, infections and anemia, controlling for a host of other potential confounders. Aizer (2006) employs instrumental variable methods to estimate the impact of violence against women on birth outcomes and finds that victimization while pregnant significantly increases the likelihood of a low birth weight birth. In addition, children who witness violence against their mothers (between 50 and 64 percent of all women report that their children routinely witnessed the abuse) are at increased risk for developmental problems including high levels of anxiety and depression, low self-esteem, and poor school performance - similar to those who have themselves been abused (WHO, 2002).

3. The cyclical nature of violent relationships

Despite the high costs of domestic violence in terms of physical and emotional injury, lost days of work and the negative impact on their children, many victims refuse to leave their batters or seek the help of authorities. Among the reasons cited by battered women for why they remain are: love of their partners, financial dependence, lack of support by third parties and fear for their safety or the safety of their children (WHO, 2002; Sagot, 2000; Strube, 1988 and references therein). In a study of victims of domestic violence in Omaha, Nebraska, nearly 60 percent of women stated that one of the reasons they remain in relationships is their love for their abusers (Dunford et al, 1990).

The decision to leave also depends on the severity and frequency of the beatings (Gelles,1976; Strube, 1988). Reasons for not reporting abuse to the authorities include considering the incident a private matter, not wanting the police or courts involved, fear of perpetrator, wanting to protect the perpetrator or the relationship and believing that the police could or would not do anything (Bureau of Justice Statistics, 1998; Tjaden and Thoennes, 2000). While these reasons are consistent with the idea of rational agents weighing the benefits and costs of leaving or reporting, a more complex picture appears once we consider the dynamics of battering.

While some women refuse to leave their batterers, perhaps just as common are women who leave their batterers multiple times only to return despite the high probability of future victimization. Past studies have found that between 25% and 75% of women seeking help in shelters return to their partners shortly after leaving the shelter.[7] Studies by psychologists provide additional evidence of this cyclical pattern (see Walker, 1979). Reasons provided for returning include: a belief that the batterer wants to change, emotional attachment, economic needs, pressure from others and fear. Interestingly, women who seek help in shelters underestimate their probability of returning to the abuser (Griffing et al., 2002). Evidence suggests that after leaving, women may experience an increased emotional attachment to their batterers, making them more likely to return (Dutton, 1995; Griffing et al., 2002). Over time women seem to learn the importance of emotional attachment: Griffing et al (2002) find that women with past

[7] See Strube (1988). When women do leave, they typically do so only after years of abuse. Tjaden and Thoennes (2000) found that victims of physical assault suffered an average of 4.5 years of victimization by the same partner, with 26.6% of the women suffering more than 5 years. On average, women suffer 7 assaults at the hands of the same partner.

experience of leaving and returning assign more importance to emotional attachment as a reason to return.[8]

Just as women leave and return to their batterers, it is also common for women who report their partners to the authorities to change their mind afterwards, dropping the charges and returning to their partners, only to be battered again in the future. Studies in the 1970s and 1980s found that among women whose husbands had been arrested for assault against them, between 50 and 90 percent requested that the charges be dropped by the prosecutor, despite evidence that women who drop charges are four times more likely to suffer future violence than those who do not.[9]

The well-documented fact that many women change their minds after leaving or reporting their partners suggests that the idea of a rational agent with stable preferences weighing the benefits and costs of leaving or reporting may not be appropriate. We believe that the dynamics of battering indicate that women's preferences change as time from the battering incident elapses. Right after the incident, the costs of remaining in the relationship are clear to the woman and her valuation of the relationship will be low. As time passes her emotional attachment to the batterer may reappear as fear is replaced by other feelings such as loneliness. Our assumption that women value the relationship less when fearful is consistent with psychological evidence on how emotional states affect the desirability of different goods or actions (see Loewenstein 1996; Read and van Leeuwen, 1998; Loewenstein et al., 2001; Gilbert et al., 2002; Wilson and Gilbert, 2003). We propose to model women in battering relationships as having time inconsistent preferences.

[8] They did not find differences across women in the other reasons for returning.
[9] See Parnas (1970), Field and Field (1973), Bannon (1975), Ford (1983) and Ford and Regoli (1992).

The cyclical character of battering relationships could be explained without relying upon changing preferences. Women could leave and return in response to changes in the likelihood of violence. Women might also leave and report as a tool to improve their bargaining position in the relationship without intending to end the relationship.[10] However, neither can explain the large number of women who initially report that they do want to end the relationship but finally return to their batterers. A third explanation may be that women have limited information about their outside opportunities and may return after they obtain better information. However, this is not completely consistent with the fact that battered women in shelters highly underestimate the likelihood of returning. Finally, cyclical behavior can in principle be explained with changing but time consistent preferences as in the rational theory of addiction (Becker and Murphy, 1988; Dockner and Feichtinger 1993; and Palacios-Huerta 2003) and the cue theory of consumption (Laibson, 1997).

A key difference between these alternative explanations of the cyclical nature of battering relationships and our theory of time inconsistent preferences revolves around the demand for commitment devices. With time inconsistent preferences there is a tension between the intentions of a woman right after a battering incident and the same woman some time after. If a woman knows that her intentions will change in the future and she dislikes the decision that she will make in the future, she may desire to commit herself to a course of action now. In contrast, these alternative explanations do not generate a demand for commitment. In the rest of the paper we provide both anecdotal and quantitative evidence that is consistent with a model in which battered women do

[10] Farmer and Tiefenthaler (1996) develop a model to explain that women might leave their abusive partners to signal that they are willing and able to end a violent relationship. However, this model explains less well the extreme cyclicality that is observed with women leaving and returning multiple times.

demand commitment devices by examining the effect of a policy that commits women to prosecute their batterer. This no-drop policy is described in the next section.

4. No-Drop policies

Over the past 25 years, local prosecutors and legislators have adopted a series of legal innovations with the objective of increasing prosecution of domestic violence. One of the most common and controversial is a "no-drop" policy which compels the prosecutor to continue with prosecution even if the victim expresses a desire to drop the charges and ceases to cooperate with the prosecution. In a survey of 50 of the largest US cities, in 1979 only one city (Omaha, Nebraska) had a no drop policy and by 1996, all but six cities had a no-drop policy. See table 1 for a listing of the cities and the year in which they adopted a no-drop policy.

In this paper we offer a rationale for adopting no-drop policies that is based on the tension between the victim's intentions at different points in time. Her preferences for prosecution and ending the battering relationship are strongest right after a battering incident. Over time, her preferences change such that she no longer wishes to prosecute and she has often reconciled with the abuser. Hence, if at the time of the battering incident she knows that she will forgive her partner and drop charges in the future, she is less likely to report him at that time. But if her power to drop charges in the future is removed (because of a no-drop policy), she may be more willing to report him. In this way, the no-drop policy provides the victim with a commitment device to overcome the time inconsistency of her preferences.

Evidence from surveys of victims supports the idea of time inconsistency of preferences and the value of no-drop policies. Smith et al. (2001) presents the following comments by victims in cities with “no drop” policies: “The prosecutor did not listen to me when I recanted my story. They continued to prosecute. In the long run, I am so glad. He got punished.” Another woman states “If it hadn’t been for the laws of arresting and prosecuting, I would have been back with him. I am glad they stuck with it and enforced the laws.”

To our knowledge, there is no scientific study of the effect of no-drop policies on the number of women who are battered, the seriousness of domestic violence assaults or the proportion of assaults that are reported.[11] However, there is evidence that this policy did represent a significant change in policy and led to an increase in prosecutions and convictions (Smith et al., 2001).

5. The model

In this section we present a simple model of domestic violence in which the woman displays changing preferences regarding the value of the relationship and is aware of this. The objective of this model is to show how providing a commitment device in the form of no-drop policies would affect both a man’s behavior and a woman’s response to it. The model provides one surprising result: implementation of no-drop policies leads to a reduction in the number of batterers who are murdered. The reason is that murder is an extreme form of a commitment device. When the government provides a cheaper one,

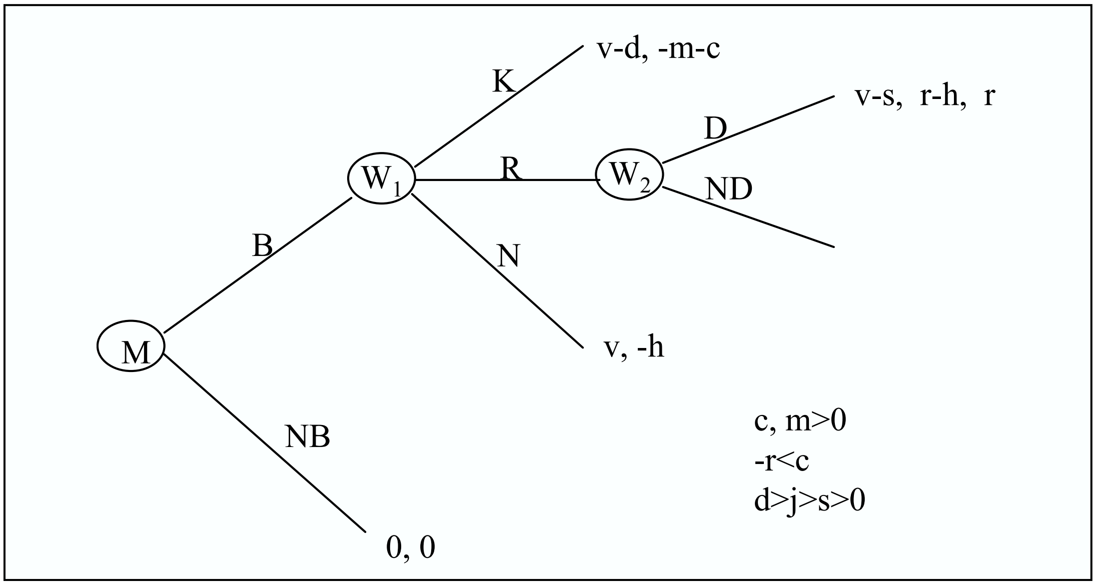
[11] Perhaps the closest is that of Dugan, Nagin and Rosenfeld (2003) who incorporate no-drop policies among other prosecutorial and police policies to create an index of “exposure reduction.” They find that too little exposure reduction may increase intimate partner homicide, while greater amounts can reduce it.

women who were willing to kill their partners to avoid returning to them, will now report them to the authorities instead. In addition the model shows that a no-drop policy results in an increase in reporting if the degree of time inconsistency is large enough and has an ambiguous effect on the amount of battering.

The model without a "no-drop" policy is depicted in Figure 1. First the man chooses between battering (*B*) or not (*NB*). Battering gives him a utility of v. We assume that this utility is randomly distributed in the real numbers –with c.d.f. $G(v)$. This assumption captures the fact that some men really enjoy battering while others dislike it. If no battering occurs the game ends and the players receive a normalized payoff of zero. If battering occurs, the woman has three options: kill her partner (K), do nothing (N), or report him to the authorities (R). If she kills him, he suffers a cost d for being dead,[12] and she faces the cost c of being prosecuted by the authorities and the loss m of the value she assigns to the relationship (this includes both the sentimental and economic value of the relationship). If she does nothing, the relationship continues. Since she has been battered her valuation of the relationship is diminished by the amount h. We assume that this utility is randomly distributed in the positive real numbers –with c.d.f. $F(h)$. This assumption captures the fact that battering affects women's valuation of the relationship differently. We assume that the man does not know the value of h when he makes his decision.

[12] We do not assume the cost of being dead is infinite since some men may be willing to batter their wives even under the serious threat of being killed by them.

Figure 1: Game Tree



We assume that reporting the battering partner to the authorities has a direct benefit (or cost) *r* to the woman. She benefits from reporting him to the authorities if the police scare him or remove him while he is still violent. Reporting him to the police may also have costs, resulting in a negative *r*. He may get upset and violent or there may be stigma costs associated with police intervention. Therefore, the parameter *r* may be positive or negative depending on whether the direct benefits or costs of reporting prevail (we assume that $-r<c$, that the cost of killing him is greater than the cost of reporting him).

If she reports him, the legal procedure starts and a new self of the woman (W_2) decides in period two whether to drop charges (D) or not (ND). Her new self (W_2) has a different valuation of the relationship than the valuation of the previous self (W_1). The payoffs of these two selves (W_1 and W_2) are written in the second and third place, respectively, in the payoff vectors for the actions D and ND. Both selves obtain the same utility level from ND and continuing with the legal procedures, *-m* in addition to *r*.[13] The first self assigns a value of *–h* to dropping the charges and staying in the relationship, while the second self values it as if nothing had happened, *0*. These payoffs are in addition to the direct benefit of reporting *r*. Note that the preferences between the woman's selfs differs in *h:* the larger *h,* the greater the degree of time inconsistency displayed by the woman.

Finally, the man (whose payoff is indicated in the first place of the payoff vector) suffers a cost of *s* if the woman reports him and then drops the charges and suffers a cost of *j* if the woman does not drop the charges. This parameter represents the expected disutility of going to jail.

We assume that the parameters *c*, *d*, *j*, *m* and *s* are positive. In addition, we assume that the worst punishment is death, followed by jail and then arrest when it is not followed by prosecution ($d>j>s$).

If a "no-drop" policy is in place the game is the same with the exception that the second self does not have the option of dropping the charges. That is, once she reports him she is committed to prosecuting him.

We study next how a "no-drop" policy would affect the behavior of the players. First, we provide a description of equilibrium behavior with and without such a policy. We follow this with a comparison of the two situations in terms of battering, and the woman's response to it.

[13] Remember that payoffs are normalized so as to have the utility if no battering occurs equal to zero.

5.1. Without a "no drop" policy:

The subgame perfect equilibrium can be solved easily by backwards induction. W_2 always drops the charge since *r-m* is lower than *r*. Knowing this W_1 must choose among kill (K), report (R) and do nothing (N). Her decision will depend on the disutility of remaining in a battering relationship (*h*) and whether reporting him has direct benefits or costs regardless of what she does later (*r* positive or negative). If *r* is positive, reporting him when she will drop the charges later is always better than doing nothing. Thus she compares K and R. She will choose to report him if $r-h>-m-c$, (the utility from reporting exceeds that of killing him). Thus, the woman reports the batterer with probability $F(r+m+c)$ and kills him with the complementary probability. If *r* is negative, reporting him when she will drop the charges later is always worse than doing nothing. Thus she compares K and N. She will choose to do nothing if $-h>-m-c$. Thus, the woman does nothing with probability $F(m+c)$ and kills him with the complementary probability. Figure 2 shows the equilibrium response to battering for both positive and negative *r* and the corresponding vector of payoff for the players as a function of *h*.[14]

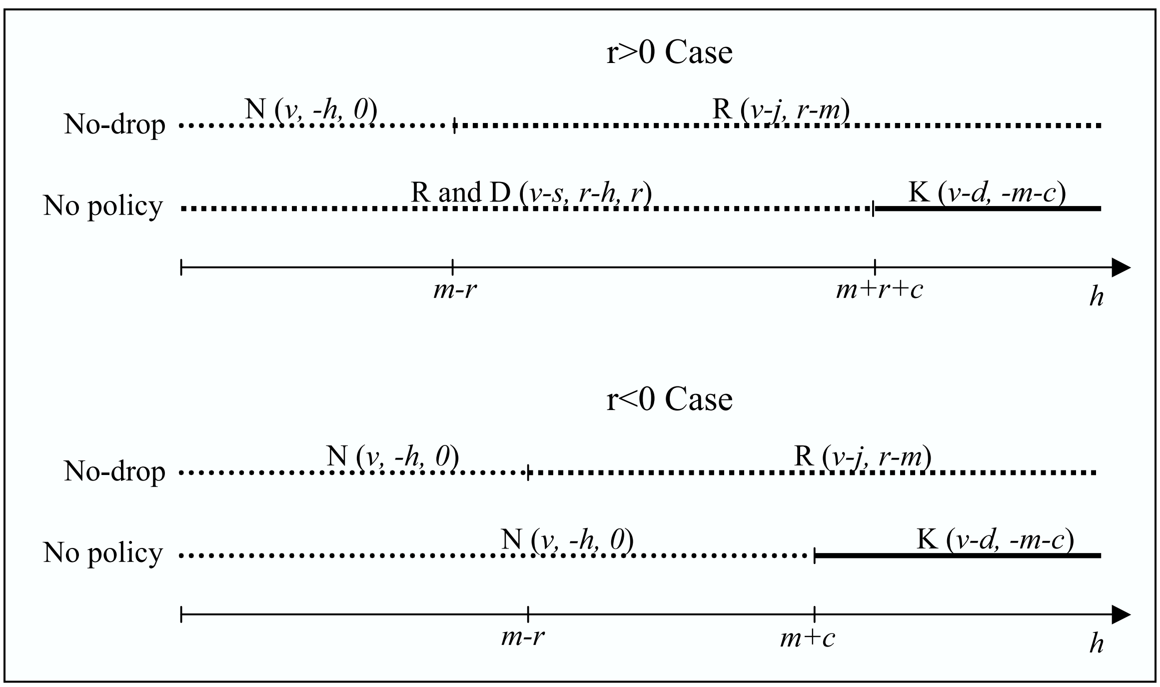
The decision of the man will depend on his expectation of the woman's response to battering. Given the distribution of men's taste for domestic violence, we have that a proportion $1-G((1-F(r+m+c))d+ F(r+m+c)s)$ will choose to batter if *r* is positive.

[14] We do not duplicate the payoff of the two selves when they coincide.

5.2. With a "No-drop" policy:

The main difference between the case without a no-drop policy and with such a policy is under the latter, reporting is always better than killing. This follows from the fact that W_2 cannot drop the charges and reporting the man is less costly than killing him ($-r<c$). Thus she compares N and R. She will do nothing if $-h>r-m$. Thus, the woman does nothing with probability $F(m-r)$ and reports him with the complementary probability. Note that the probability of reporting him is increasing in r and decreasing in m. Then, we have that a proportion $1-G((1-F(m-r))j)$ of men will choose to batter.

Figure 2: Equilibrium Actions for the Woman



5.3. The effects of the "no drop" policy:

From the comparison of the ranges of h that result in a battering man being killed we obtain the following proposition. The result follows directly from Figure 2.

Proposition 1: A no-drop policy reduces the probability that a battering man is killed.

The intuition for this result is as follows. Without a "no-drop" policy the woman knows that she will drop the charges in the future, therefore reporting him to the authorities will not end the relationship. The only way she has to commit herself to ending the relationship is by killing him. She will do so if her valuation of her future life with the batterer (m-h) is low enough. If instead a "no drop" policy is in place, reporting him to the authorities serves as a commitment device since she will not be able to drop charges.

From Figure 2 we can also study the effect of the "no drop" policy on the reporting of battering.

Proposition 2: A no-drop policy increases the reporting if the degree of time inconsistency is large enough ($h>m-r$) but may have a negative effect otherwise.

If reporting a batterer to the police provides a short run cost to the woman but no benefit ($r<0$) the intuition is straight forward. The woman knows that withoug the policy she will drop the charges later and thus will not report him after the battering. If instead she cannot drop the charges later she may be willing to report him as a way to commit herself to ending the relationship. Moreover, a no-drop policy may increase reporting since some women (those with an extremely high h) will decide to report the batterer instead of killing him.

Contrary to what would be obtained under the assumption of stable preferences in this model, restricting the set of choices attached to reporting for a woman with unstable preferences may actually increase the reporting of battering incidents. However, when the degree of time inconsistency is sufficiently low ($h<m-r$) and there are short run benefits of reporting ($r>0$) no-drop policies actually decrease reporting. In this case, women are willing to report battering to obtain the short run benefit but are not willing to commit to prosecution, hence, they would report without a "no drop" policy but not with such a policy in place.

Proposition 3: A no-drop policy has an ambiguous effect on the amount of battering.

The decision to batter depends on women's response to battering. On the one hand, from proposition 1, we know that a "no drop" policy will result in a lower probability of the batterer being killed. Since this is the harshest punishment possible, a "no drop" policy can actually make battering more attractive. In addition, such a policy may result in fewer cases being reported if the degree of time inconsistency is small, which would also make battering more attractive. On the other hand, there are cases in which a "no drop" policy will increase the number of cases reported and prosecuted since charges cannot be dropped, and this would make battering less attractive. The total effect will depend on the relative strength of the different forces.

While this simple model of domestic violence shows that the effect of no-drop policies on battering is theoretically ambiguous, its effect on the murder of batterers is not. When a woman displays time inconsistent preferences and exhibits some degree of sophistication regarding her inconsistency (eg, she can anticipate the inconsistency) she may be willing to commit herself to ending the relationship. If the government does not provide such a commitment option, she may prefer to kill her batterer rather than remain in the violent relationship. Hence, a non-ambiguous result of the model is that “no drop” policies diminish the number of batterers murdered by their partners.

Moreover, if preferences display a large enough degree of time inconsistency, the effect of no-drop policies on reporting is positive since women may start reporting knowing that they will not be able to drop charges in the future.

6. Empirical Analysis

In this section we estimate the impact of no-drop policies on intimate partner homicide, underlying violence against women and the reporting of battering. We proceed in two stages. First, we estimate the impact of no-drop policies on intimate partner homicide using data on the 48 largest cities in the US for the period 1979-1996. Second, we estimate the impact of no-drop policies on the number of women admitted to the hospital for an assault (an alternative and less extreme measure of domestic violence than homicide) and arrests for domestic violence (our measure of reporting) for the seven largest counties in California (because these data are not available for the 48 cities).

6.1. The impact of no-drop policies on intimate partner homicide

6.1.1. Data

Our data for this part of the analysis includes information on prosecutorial and police policies regarding domestic violence (including the presence of no-drop policies), services for domestic violence victims and intimate partner homicides in 48 of the largest

US cities for the period 1979-1996.[15] For our analysis, two cities were dropped (New York City and Baltimore) because of ambiguity in the definition of the city and the resulting difficulty linking these cities with other data.[16]

Data on intentional homicides by intimate partners come from the FBI Uniform Crime Reports Supplemental Homicide Reports (SHR) 1979-1996. A homicide was considered an intimate partner homicide if the assailant was a husband (wife), ex-husband (ex-wife), common law husband (common-law wife), or boyfriend (girlfriend). Homicide by an ex-boyfriend (ex-girlfriend) is not recorded. The small number of intimate partner homicides in which the victim and assailant were of the same sex was dropped. These data also do not contain unintentional or negligent killings – all homicides included here were intentional. Intimate partner homicide figures were adjusted by the FBI for missing data on relationship assuming underreporting independent of sex, race and marital status of the victims.[17] We keep all homicides victims between the ages of 20 and 55 (the age group for which intimate homicide is most prevalent).

Figures 3A and 3B display trends in intimate partner homicide for the 48 cities and the nation as a whole for the period 1979-1996. As is evident from the graphs, the trends are similar for our sample and the nation as a whole suggesting that our results are likely generalizable. While the annual number of female intimate partner homicides nationally has declined slightly from 1500 to 1250 over the nearly 20 year period, the number of

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[15]The data on prosecutorial policies and services were collected by Laura Dugan, Daniel Nagin and Richard Rosenfeld for the National Institute of Justice and the National Consortium on Violence Research. See Dugan, Nagin and Rosenfeld (2000) and (2003).
[16] For example, New York City consists of five counties, each with a different prosecutor.
[17] This would result in an over-reporting of intimate homicide victims if stranger homicides are less likely to have missing data on relationship to the assailant.

men killed by wives has declined dramatically from 1400 to less than 500 annually. Other studies have shown that more than half of men killed by their partners had documented histories of battering.[18] If we interpret the number of women killed by intimates as a reflecting the amount of underlying domestic violence, then the fact that this number has remained relatively constant suggests that the decline in the number of men killed is not attributable to a decline in domestic violence.

6.1.2. Results

In Figure 4 we present the average number of men and women killed by intimates over this period in the years immediately before and after a no-drop policy was adopted (t=0 in the year the policy is adopted, t= -1 in the year before and t=1 in the year after).[19] As is evident from the graph, there is a decline in the number of men killed by women in the years immediately after the adoption of a no-drop policy. In contrast, the number of women killed by their partners appears, if anything, to increase with the adoption of no-drop policies (though not significantly) and then decline. Prior to the adoption of the policy, there does not appear to be any downward trend in the intimate homicide rate suggesting that passage of the law does not simply reflect underlying trends.

In Table 2A we present estimates of the impact of no-drop policies on male and female victims of intimate partner homicide controlling for other characteristics that could also affect intimate homicide rates. We employ log-linear regressions as well as

[18] A study conducted in Georgia of 226 female inmates imprisoned for having killed an intimate partner found that 90 percent of women claimed that the victim assaulted or abused her at the time of the crime and in more than 50 percent of the cases there was a record of a history of domestic abuse. See Haley (1992).
[19] Numbers represent the (weighted) average number of homicides per city for the 30 cities that passed a no-drop policy 1981-1994.

negative binomial regression models following Grogger (1990) which yield similar results.[20] All regressions include the log of the population age 20-55 (we do not constrain the coefficient to be equal to 1) and city and year fixed effects and are weighted by the population of the city.

In column 1 of Table 2A we present results of a regression of the natural log of males killed by intimate partners on an indicator for whether a no-drop policy was in place in that year controlling for city and year fixed effects as well as the natural log of the population of men age 20-55, the share black, and the rate of non-intimate homicides. The estimate of the impact of no-drop policy of -.188 is statistically significant. In contrast, in column 2 we find that no drop policies have a positive (0.117) but insignificant impact on homicide of females by intimate partners. In columns 3-8, we present the results of regressions that include additional controls: average area wages, the employment to population ratio, AFDC benefits for a family of four in the state, services for domestic violence victims, and the lag of the number of women killed by their partners as a control for changes in underlying domestic violence.[21] As is evident from the table, inclusion of these additional controls does not significantly alter the negative and significant relationship between no-drop policies and the number of men killed by intimates.[22] In the second panel of the table are results of the negative binomial

[20] Poisson models were rejected due to over-dispersion (the variance exceeded the mean in these data). When there is over-dispersion, Poisson estimates are inefficient with standard errors biased downward. The negative binomial distribution can be thought of as a Poisson distribution with unobserved heterogeneity which, in turn, can be conceptualized as a mixture of two probability distributions, Poisson and Gamma.
[21] With the exception of population counts and share black in the city, data for the above controls are collected annually and thus are not merely linear interpolations between census years. This is important as we are identifying the impact of no-drop policies off a non-linear change in policy.
[22] As a "falsification" check, we also estimate the impact of no-drop policies on non-intimate partner homicide. When we do, the point estimate from a log-linear regression is -0.061 and it is imprecisely estimated with a standard error of 0.046.

specification in which the outcomes are the number of male and female intimate partner homicides.[23] The results are very similar to those from the log linear regressions.

We also estimate the impact of no drop policies on intimate partner homicide stratified by age of the victim. We argue that if no-drop policies are decreasing male homicides because of substitution of commitment devices, then we should find greater effects among those in longer relationships which would allow women time to learn of their difficulty committing. While we lack information on relationship tenure, we do have information on the age of the victim which serves as a very crude proxy for relationship length: younger victims are more likely to be in shorter relationships relative to older victims.

In Table 2B we present the results of a log-linear specification stratified by age of the victim. We define as old, victims age 35-54 and as young, victims age 20-34. As is evident from the table, we find that the impact of no drop policies on intimate partner homicide is limited (and considerably stronger) for older victims, consistent with the notion that women need time to learn of their difficulty to commit to leaving without any commitment device.

6.1.3 Robustness

[23] Hausman, Hall and Grilliches (1984) propose a conditional negative binomial model for panel data. However, Allison and Waterman (2002) argue that this model is not a true fixed effect method because conditioning on the total count for each city does NOT eliminate the intercept from the likelihood function. Rather, Allison and Waterman argue and provide simulation results that suggest that an unconditional negative binomial regression that includes dummy variables for the city fixed effects yields unbiased estimates. The unconditional negative binomial regression results with dummy variables for the fixed effects that are presented in Table 2A are similar to the log linear results and the conditional negative binomial model (xtnbreg in STATA) are considerably smaller (roughly half the size of the unconditional estimates) but significantly different from zero.

When we employ a log-linear model, we necessarily exclude from the analysis any observation in which there are no intimate partner homicides. These tend to be smaller cities which receive small weights in the weighted regressions. To check whether our results are driven largely by these excluded observations, in Table 2C we present results in which we add 1 to the dependent variable so that the observations previously dropped are now included (and equal to zero). We do this for the subsample of older victims as there are more dropped zeros than for the general sample. The results are similar, though smaller.

It may be the case that the adoption of no-drop policies coincides with the adoption of other policies that address domestic violence, in which case our estimates of the impact of no-drop policies on intimate partner homicide may suffer from omitted variable bias. To address this issue, in Table 3 we present estimates of the impact of no-drop policies on intimate partner homicide controlling for additional domestic violence policies. These policies include: whether the police have a separate domestic violence unit, whether there is a "pro-arrest" police for violation of a protection order and whether the city has what is referred to as a "mandatory arrest policy" which states that when an officer suspects domestic violence, he must arrest the offender. In the first two columns of Table 3 are estimates based on the entire sample and in columns five and six the estimates are based only on older victims. As is evident from the table, the addition of these controls does not appear to have any effect on the impact of no-drop policies on intimate partner homicides. This also provides evidence that the reduction in male homicides as a result of no-drop policies does not merely reflect a shift or change in the seriousness with which the authorities take issues of domestic violence. If it did, the other policies would have a similar effect. Finally, we include controls for male and female labor force participation, earnings and education in columns three and four and seven and eight. In contrast to most of the other controls, these are not collected annually but are intercensal linear interpolations. The results are very similar.

To assess the extent to which the results may be driven by one city, we estimate 48 separate log linear regressions dropping one city from each. We present the resulting distribution of estimates of the coefficient on no-drop policies in Table 4A. The median estimate is -0.213 with a 95 percent confidence interval of [-.217, -.208]. We therefore conclude that it is not the case that the results are driven by one city.

An additional concern is that the estimates of the effect of no-drop policies may be capturing downward trends in homicides which are not controlled by year fixed effects. As an additional check to assess whether this may be driving our results, we randomly generate no-drop policies and estimate the impact of these randomly generated laws on male and female intimate partner homicide. We repeat this exercise 1000 times. The results are presented in Table 4B. As is evident from the results, the randomly generated no drop policy has no significant impact on either the number of men or women killed by intimates which suggests that the significant results that we obtain are not driven by downward trends in homicides unrelated to the adoption of no-drop policies.

The data support the prediction of our model that the number of batterers who are murdered unambiguously declines with the adoption of no-drop policies. Our findings with respect to females are inconclusive (consistent with our model that provides no prediction with respect to the effect of no-drop policies on domestic violence). Not only are the effects insignificant, but they refer only to extreme acts of violence. Thus, to empirically assess the extent to which no-drop policies affect underlying domestic violence and reporting, we turn to a subset of the data for seven counties in California for which we have additional information.

6.2. Impact of no-drop policies on underlying violence and reporting

6.2.1. Data

For our analysis of the impact of no drop policies on underlying domestic violence and reporting, we focus on the seven largest counties in California, representing 63 percent of the state, for which we have information on the presence of no-drop policies as well as the number of men arrested for domestic violence (our measure of reporting) and the number of women admitted to the hospital as a result of an assault (our measure of underlying violence). [24] These data are available by race, county and year for the period 1990-2000.[25]

Our measures of reporting and underlying violence are proxies. Data on actual reports by the victims are not available – though evidence suggests that over the period of the 1990s as more cities adopted no-drop policies, the share of victims reporting the

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[24] The seven counties are: Alameda, Fresno, Los Angeles, Sacramento, San Diego, San Francisco and Santa Clara. Together they represent 19 million individuals or 63 percent of the population of California. In all but Los Angeles and San Diego counties, there is only one prosecutor for the entire county so that the presence (or absence) of a no-drop policy applies to all residents in the county (not just those in the largest city). In Los Angeles and San Diego counties, the cities of Los Angeles and San Diego have a separate prosecutor and the information we have on the presence of no-drop policy refers to the city prosecutor, (although it is important to note that 40 percent of the population in Los Angeles and San Diego counties live in Los Angeles and San Diego city, respectively). We consider the measurement error introduced by this in the analyses.

[25] The data on arrests for domestic violence were collected by William Wells and Willian DeLeon-Granados for the California Department of Justice, Criminal Justice Statistics Center. The data on admissions to the hospital for an assault were calculated by the authors from the California hospital discharge database.

victimization to the police increased from 48 to 56 percent (Greenfeld et al, 1998). Nor do we have measures of the incidence of domestic violence. Instead, we use the number of women admitted to the hospital for an assault as a proxy for underlying violence, eventhough it is an imprecise measure for two reasons. First, it includes all women admitted to the hospital for assault and therefore includes those assaulted by non-intimates. Second, it includes only those for whom the injuries were serious enough to warrant hospital admission and excludes all women who were assaulted but did not seek medical attention. We do believe, however, that it is a useful measure for three reasons: 1) it is the only local-area measure of violence available (and it is available by race and year); 2) it is devoid of any reporting bias as it does not depend on women admitting that they were battered by their partners and 3) since a high proportion of women (76-87 percent) who are assaulted are assaulted by an intimate, most hospital admissions for assault will likely have been caused by an intimate.[26]

To identify the impact of no-drop policies on domestic violence against women and reporting, we use variation across the seven different counties in California for the period 1990-2000. Four of the counties had a no-drop policy in place by 1990. Three of the counties adopted a no-drop policy during the study period (Santa Clara adopted in 1991 and Alameda and Fresno each adopted in 1994). Our estimate of the impact of no-drop policies on violence and reporting is therefore a difference-in-differences estimate comparing the difference (before and after) in outcomes for the those counties that adopt

[26] Estimates from the NVAWS suggest 76 percent while evidence from a medical chart review of pregnant women admitted to the hospital for assault and presented by Goodwin and Breen (1990), suggests 87 percent.

a no-drop policy with the difference in outcomes over the same period for those counties that observed no change in their no-drop policy.

6.2.2. Results

In Table 5 we present regression estimates of the impact of no-drop policy on violence against women from log-linear regression models (columns 1-2) and negative binomial models (columns 6-7) that include many controls. For all regressions in this table, county fixed effects and quadratic time trends are included as well as time-varying county specific controls for differences in population growth, per capita income, the employment to population ratio, non-intimate homicide and the number of shelters available for victims of domestic violence. We find no significant impact of no-drop policies on violence as measured by the log of the number of women admitted to the hospital as a result of assaults (column 1). As a "falsification check" we also estimate the effect of no-drop policies on hospitalization for car crashes and, as expected, we find no effect (column 2). We find similar results with the negative binomial regressions. Having established that no-drop policies do not appear to have any impact on underlying violence, we turn to estimating their impact on reporting.

In Figure 5 we present a measure of reporting domestic violence (the number of men arrested for domestic violence) in the years immediately before and after a no-drop policy was adopted (t=0 in the year the policy is adopted, t= -1 in the year before and t=1 in the year after). As is evident from the graph, there is a large increase in this ratio in the years immediately after the adoption of a no-drop policy. Prior to the adoption of the policy, there does not appear to be much change in reporting, suggesting that the passage of the law does not simply reflect underlying trends.

To control for any other changes that might have been coincident with the adoption of no-drop policies and could influence arrest rates, we turn to regression analysis. In column 3 of Table 5 we examine the impact of no-drop policies on reporting as measured by the natural log of the number of arrests including all controls mentioned above. We find that counties that adopt a no-drop policy witness a 14-17 percent higher rate of arrest for domestic violence relative to counties that do not adopt such a policy over this period. However it is not clear from this analysis if this finding is due to an increase in reporting, or an increase in domestic violence as a result of no-drop policies, (though the evidence suggests that domestic violence did not increase with the adoption of no-drop policies). Thus in columns 4 we estimate the impact of no-drop policies on arrests controlling for violence against women (as measured by female assaults). We find that no-drop policies still increase arrests by 14 percent. Finally, we attempt to control for police policies that might be correlated with no-drop policies and arrest rates. However, unlike prosecutor offices which tend to be county-wide, police departments are more local in nature and as such their policies with respect to domestic violence also vary at a more local level than the county. We only have information on the police policies of the largest city in each county, but we include an indicator for whether that city had a mandatory arrest policy in place in column 5.[27] When we do, we find that mandatory arrests have a very small and insignificant negative effect on arrests for domestic violence and do not alter the impact

[27] Oakland and Fresno adopted mandatory arrest in 1993, LA and San Diego had such a policy in place in 1990 (the beginning of our sample), San Francisco never adopted one, San Jose adopted in 1994 and Sacramento in 1996.

of no-drop policies on outcomes. We find similar results with the negative binomial regressions.

As noted previously, two of the seven counties (LA and San Diego) have more than one prosecutor's office and our measure of no-drop policies refers to the largest city in each county, introducing considerable measurement error if another city within either county should change its no-drop policies during this period. This did in fact happen in Los Angeles. Within Los Angeles County, LA City (the largest municipality in LA County) adopted a no-drop policy in 1986 (before the start of our sample) but Long Beach City, which is a much smaller part of Los Angeles County, adopted in 1991.[28] Since statistics on arrests for domestic violence are not available separately for LA City and Long Beach, by including LA County in our regressions, we are introducing measurement error. To address this we exclude LA County from the sample and present the results in the second panel of Table 5. Our estimates of the impact of no-drop policies on arrests increase considerably (likely as a consequence of the reduction in measurement error) but do not change for assaults. In the third panel of Table 5 we exclude both LA county and San Diego counties, although we have no evidence that any other city in San Diego county changed its no-drop policy during this period. The results are similar to previous estimates.

7. Conclusions

Motivated by the cyclicality of violent relationships we present a theory of domestic violence that incorporates time inconsistent preferences. Our theory predicts

[28] As of 2000, 9.5 million reside in LA County of which 461,000 reside in Long Beach and 3.7 million in LA City.

that the adoption of no-drop policies would result in an increase in the reporting of battering to the authorities and, more surprisingly, a decrease in the murder of violent partners. The reason for the latter is that no-drop policies provide to women in battering relationships a cheaper commitment to end the relationship than murder.

Consistent with our theory we provide evidence that the adoption of no-drop policies in the US have resulted in a reduction of male homicides by intimates and an increase in reporting of battering. Unfortunately, we find that no-drop policies have had no effect on the prevalence of domestic violence as measured by female hospitalizations for assault, although this measure is far from perfect.

Our results underscore the importance of considering the value of commitments when evaluating policies. In particular, we provide evidence that agents may substitute a cheaper public commitment device when one is offered for a more expensive private one.

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Table 1: Year No-Drop Policy Adopted by City

City	year no drop	2000 pop
Albuquerque	1987	448,607
Atlanta	1983	416,474
Austin	1994	656,562
Baltimore	1987	651,154
Boston	1992	589,141
Buffalo	1995	292,648
Charlotte	1993	540,828
Chicago		2,896,016
Cincinnati	1995	331,285
Cleveland	1992	478,403
Columbus		711,470
Dallas	1995	1,188,580
Denver	1986	554,636
Table 4B: Ranc	1994	951,270
El Paso	1989	563,662
Fort Worth		534,694
Honolulu		371,657
Houston		1,953,631
Indianapolis		791,926
Jacksonville		735,617
Kansas City		441,545
Long Beach		461,522
Los Angeles		3,694,820
Memphis	1995	650,100
Miami	1986	362,470
Milwaukee	1994	596,974
Minneapolis	1993	382,618
Nashville	1994	569,891
New Orleans	1996	484,674
New York	1990	8,008,278
Oakland	1994	399,484
Oklahoma City	1996	506,132
Omaha	1976	390,007
Philadelphia		1,517,550
Phoenix	1984	1,321,045
Pittsburgh		334,563
Portland	1987	529,121
Sacramento	1984	407,018
San Antonio	1990	1,144,646
San Diego	1984	1,223,400
San Francisco	1989	776,733
San Jose	1994	894,943
Seattle		563,374
St Louis		348,189
Toledo	1988	313,619
Tucson	1996	486,699
Tulsa	1996	393,049
Virginia Beach	1996	425,257
Washington	1996	572,059
Total		43,858,041
US population		281,421,906
Percent of total		15.6%

Table 2A: Impact of No-Drop Policies on Intimate Homicides

Log-Linear Regression	Male	Female	Male	Female	Male	Female	Male	Female
No-drop policy	-0.188	0.116	-0.167	0.144	-0.176	0.137	-0.193	0.117
	[0.103]	[0.084]	[0.096]	[0.094]	[0.097]	[0.095]	[0.091]	[0.091]
Ln(population)	1.943	1.057	1.904	0.876	1.923	0.897	1.956	0.557
	[0.385]	[0.376]	[0.387]	[0.378]	[0.391]	[0.383]	[0.437]	[0.416]
Control for share black & non-intimate homicide	Y	Y	Y	Y	Y	Y	Y	Y
Control for county wages, employment:population & AFDC benefits			Y	Y	Y	Y	Y	Y
Control for services					Y	Y	Y	Y
Control for ln(lag women killed)							Y	Y
Observations	689	760	689	760	689	760	649	718
R-squared	0.78	0.77	0.78	0.78	0.78	0.78	0.77	0.78

Negative Binomial Regression	Male	Female	Male	Female	Male	Female	Male	Female
No-drop policy	-0.174	0.113	-0.169	0.136	-0.146	0.133	-0.167	0.102
	[0.082]	[0.072]	[0.082]	[0.073]	[0.084]	[0.072]	[0.086]	[0.072]
Ln(population)	1.61	0.432	1.6	0.271	1.599	0.27	1.962	0.177
	[0.394]	[0.367]	[0.398]	[0.365]	[0.393]	[0.365]	[0.403]	[0.394]
Control for share black & non-intimate homicide	Y	Y	Y	Y	Y	Y	Y	Y
Control for county wages, employment:population & AFDC benefits			Y	Y	Y	Y	Y	Y
Control for services					Y	Y	Y	Y
Control for ln(lag women killed)							Y	Y
Observations	810	810	794	794	794	794	749	749
Interpretation	-16.0%	12.0%	-15.5%	14.6%	-13.6%	14.2%	-15.4%	10.7%

City and year fixed effects included in all regressions
robust standard error in brackets

Table 2B: Impact of No-Drop Policies on Intimate Homicides Stratified by Age of the Victim, Log-Linear Specification

Older Victims (35-55)	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
No-drop policy	-0.252	0.145	-0.248	0.156	-0.255	0.151	-0.29	0.138	-0.261	0.157
	[0.110]	[0.091]	[0.110]	[0.091]	[0.111]	[0.089]	[0.121]	[0.104]	[0.111]	[0.090]
Ln(population)	1.788	1.052	1.706	0.908	1.719	0.922	1.786	0.655	1.984	0.91
	[0.334]	[0.313]	[0.346]	[0.326]	[0.348]	[0.327]	[0.435]	[0.439]	[0.375]	[0.378]
Control for share black & non-intimate homicide	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Control for county wages, employment:population & AFDC benefits			Y	Y	Y	Y	Y	Y	Y	Y
Control for services					Y	Y	Y	Y	Y	Y
Control for ln(lag women killed)							Y	Y		
Control for ln (lag women killed by partners +1)									Y	Y
Observations	634	708	634	708	634	708	468	524	595	674
R-squared	0.72	0.71	0.72	0.71	0.72	0.71	0.71	0.69	0.72	0.7

Younger Victims (20-34)	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
No-drop policy	0.097	0.047	0.099	0.06	0.086	0.054	0.039	0.067	0.05	0.063
	[0.104]	[0.073]	[0.103]	[0.073]	[0.099]	[0.074]	[0.106]	[0.080]	[0.099]	[0.074]
Ln(population)	0.71	1.391	0.685	1.277	0.704	1.276	0.919	1.314	0.806	1.195
	[0.350]	[0.313]	[0.361]	[0.314]	[0.363]	[0.313]	[0.454]	[0.355]	[0.402]	[0.336]
Control for share black & non-intimate homicide		Y	Y	Y	Y	Y	Y	Y	Y	Y
Control for county wages, employment:population & AFDC benefits			Y	Y	Y	Y	Y	Y	Y	Y
Control for services					Y	Y	Y	Y	Y	Y
Control for ln(lag women killed)							Y	Y		
Control for ln (lag women killed by partners +1)									Y	Y
Observations	636	805	636	805	636	805	529	669	600	766
R-squared	0.72	0.76	0.72	0.76	0.72	0.76	0.73	0.75	0.73	0.75

Robust standard errors in brackets

Table 2C: Impact of No-Drop Policies on Intimate Homicides Among Older Couples (age 35-54) Log-Linear Specification Adding 1 to the Dependent Variable

	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female
No-drop policy	-0.197	0.099	-0.192	0.105	-0.186	0.105	-0.19	0.111	-0.269	0.074	-0.19	0.112
	[0.085]	[0.073]	[0.084]	[0.073]	[0.083]	[0.073]	[0.084]	[0.073]	[0.093]	[0.085]	[0.084]	[0.073]
Ln(population)	1.337	1.086	1.273	1.006	1.259	1.005	1.515	0.902	1.547	0.65	1.534	0.881
	[0.238]	[0.234]	[0.244]	[0.245]	[0.245]	[0.247]	[0.265]	[0.274]	[0.316]	[0.320]	[0.266]	[0.280]
Control for share black and non-intimate homicide rate	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Control for county wages & employment:population			Y	Y	Y	Y	Y	Y	Y	Y	Y	Y
Control for services (hotlines/shelters)					Y	Y	Y	Y	Y	Y	Y	Y
Control for lag women killed by partners							Y	Y				
Control for ln (lag women killed by partners)									Y	Y		
Control for ln (lag women killed by partners +1)											Y	Y
Observations	941	941	941	941	941	941	895	895	667	667	895	895
R- Squared	0.73	0.71	0.73	0.71	0.73	0.71	0.72	0.7	0.72	0.7	0.72	0.7

Robust standard errors in brackets

Table 3: Impact of No-Drop Policies on Intimate Homicides Controlling for Other Domestic Violence Policies

	All				Older Victims			
	Male	Female	Male	Female	Male	Female	Male	Female
No-drop policy	-0.201	0.098	-0.16	0.099	-0.254	0.1	-0.199	0.158
	[0.101]	[0.093]	[0.083]	[0.099]	[0.111]	[0.093]	[0.115]	[0.096]
ln (population)	2.319	1.105	2.133	1.01	2.835	1.456	2.377	1.256
	[0.537]	[0.591]	[0.518]	[0.665]	[0.557]	[0.525]	[0.785]	[0.732]
Share population black	-0.007	-0.008	-0.028	-0.028	-0.022	-0.011	-0.034	-0.019
	[0.043]	[0.018]	[0.032]	[0.016]	[0.015]	[0.014]	[0.019]	[0.019]
Adult non-intimate homicides per 10000	0.254	0.226	0.249	0.217	0.186	0.147	0.172	0.14
	[0.175]	[0.124]	[0.179]	[0.136]	[0.065]	[0.065]	[0.068]	[0.067]
Average wage in county	-0.007	-0.03	-0.003	-0.018	0.007	-0.014	-0.012	-0.015
	[0.019]	[0.019]	[0.020]	[0.022]	[0.014]	[0.014]	[0.026]	[0.026]
Employment:population in county	0.984	-0.024	0.068	-0.173	0.53	-0.575	-0.447	-1.208
	[1.005]	[0.781]	[0.998]	[0.879]	[0.550]	[0.565]	[0.599]	[0.608]
AFDC benefits (family of 4)	-0.001	-0.002	-0.002	-0.002	-0.001	-0.001	-0.002	-0.001
	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]	[0.001]
Ln(dv hotlines)	-0.032	-0.038	-0.032	-0.035	-0.044	-0.11	-0.084	-0.137
	[0.053]	[0.053]	[0.042]	[0.044]	[0.040]	[0.035]	[0.060]	[0.063]
Lag women killed by partners	0.007	0.006	0.06	0.04	-0.003	-0.003	-0.047	0.003
	[0.005]	[0.004]	[0.052]	[0.037]	[0.012]	[0.013]	[0.049]	[0.048]
Police pro-arrest policy for PO violation	-0.129	0.016	-0.114	0.01	-0.298	0.143	-0.305	0.127
	[0.108]	[0.118]	[0.079]	[0.141]	[0.100]	[0.112]	[0.104]	[0.115]
Police mandatory arrest for dv	0.024	-0.016	0.066	0.022	-0.089	-0.09	-0.015	-0.075
	[0.111]	[0.121]	[0.095]	[0.142]	[0.110]	[0.110]	[0.113]	[0.115]
Police domestic violence unit	-0.105	-0.112	-0.13	-0.108	-0.361	-0.287	-0.411	-0.242
	[0.113]	[0.086]	[0.124]	[0.080]	[0.126]	[0.120]	[0.125]	[0.122]
Female labor force participation			6.792	5.17			0.105	0.036
			[4.480]	[5.219]			[0.051]	[0.043]
Male labor force participation			-10.106	-5.001			-0.011	0.038
			[5.272]	[4.348]			[0.093]	[0.085]
Male median earnings			0.053	0.055			7.876	9.268
			[0.051]	[0.051]			[4.823]	[4.426]
Female median earnings			-0.119	-0.103			-11.732	-6.434
			[0.091]	[0.092]			[4.387]	[4.481]
% of men 25 + with at least 4 yrs college			-0.027	-0.048			0.037	0.048
			[0.028]	[0.051]			[0.036]	[0.036]
% of females 25 + with at least 4 yrs college			0.181	0.078			0.098	-0.027
			[0.047]	[0.047]			[0.047]	[0.048]
Observations	633	701	633	701	502	573	502	573
R-squared	0.78	0.78	0.79	0.78	0.74	0.71	0.75	0.71

Robust standard errors in brackets
City and year fixed effects included in all regressions

Table 4A: Dropping 1 City at a Time Log Linear Regression - Distribution of Coefficients

	Males
Minimum	-0.133
Maximum	-0.219
Median	-0.189
Mean	-0.188
Standard Deviation	0.017
95 % CI	[-0.193, -0.183]

Table 4B: Randomly Generated No-Drop Policy - Distribtion of Coefficients based on 1000 Simulations

	Males	Females
Minimum	-0.184	-0.202
Maximum	0.178	0.232
Mean	-0.0024	-0.0015
Standard Deviation	0.071	0.061
95 % CI	[-0.0025, 0.0020]	[-0.0017, 0.0023]

Table 5: Impact of No-Drop Policies on Violence Against Women and Arrests for Domestic Violence

	Log-Linear Regressions					Negative Binomial Regressions				
All Counties	Ln(female assaults)	Ln(car crashes)	Ln(arrests)	Ln(arrests)	Ln(arrests)	Female assaults	Car crashes	Arrests for Domestic Violence	Arrests for Domestic Violence	Arrests for Domestic Violence
No-drop policy	-0.034	0.002	0.139	0.143	0.168	-0.002	-0.045	0.163	0.104	0.132
	[0.090]	[0.043]	[0.063]	[0.063]	[0.061]	[0.02]	[0.90]	[0.052]	[0.051]	[0.065]
Per capita income	0	0	0	0	0	0	0	0	0	0
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[4.10]	[2.26]	[0.000]	[0.000]	[0.000]
Employment:population	2.853	1.714	2.253	1.935	2.225	3.328	4.584	-1.042	-3.712	-3.553
	[1.545]	[0.901]	[1.194]	[1.170]	[1.364]	[3.48]	[4.91]	[1.096]	[0.999]	[0.970]
Non-Intimate Homicide Rate	0.008	0	0.001	0	0	0.024	0.017	0.019	0.002	0.002
	[0.001]	[0.001]	[0.002]	[0.002]	[0.002]	[7.63]	[7.52]	[0.003]	[0.003]	[0.003]
Female population						0	0	0	0	0
						[14.63]	[15.87]	[0.000]	[0.000]	[0.000]
Shelters for victims of DV	-0.044	-0.001	-0.011	-0.006	-0.008	-0.036	0.039	-0.045	0.009	0.005
	[0.031]	[0.021]	[0.014]	[0.014]	[0.014]	[1.39]	[1.93]	[0.027]	[0.031]	[0.031]
White	-1.775	-0.284	-1.639	-1.433	-1.428	-0.208	1.268	0.103	-0.114	-0.106
	[0.117]	[0.074]	[0.107]	[0.177]	[0.178]	[0.99]	[7.65]	[0.167]	[0.136]	[0.136]
Hispanic	-1.507									
	[0.104]	[0.059]	[0.106]	[0.178]	[0.178]	[3.19]	[3.43]	[0.124]	[0.105]	[0.104]
Ln(female population)	1.102	1.048	1.143	1.015	1.015					
	[0.053]	[0.028]	[0.078]	[0.138]	[0.138]					
Ln(female assaults)				0.116	0.113					
				[0.079]	[0.079]					
Female assaults									0.003	0.003
									[0.000]	[0.000]
Mandatory arrest policy					-0.051					-0.054
					[0.077]					[0.068]
Observations	231	231	224	224	224	231	231	231	231	231
R-squared	0.97	0.99	0.92	0.92	0.92					
Interpretation						-0.2%	-4.4%	17.7%	11.0%	14.1%
Without Los Angeles County	Ln(female assaults)	Ln(car crashes)	Ln(arrests)	Ln(arrests)	Ln(arrests)	Female assaults	Car crashes	Arrests for Domestic Violence	Arrests for Domestic Violence	Arrests for Domestic Violence
No drop policy	-0.1	0.036	0.148	0.157	0.198	-0.032	-0.041	0.22	0.135	0.15
	[0.093]	[0.041]	[0.090]	[0.088]	[0.076]	[0.39]	[0.84]	[3.33]	[2.35]	[0.061]
Per capita income	0	0	0	0	0	0	0	0	0	0
	[0.000]	[0.000]	[0.000]	[0.000]	[0.000]	[3.68]	[2.32]	[0.59]	[0.60]	[0.000]
Employment:population	7.071	1.774	0.082	-0.559	0.159	4.457	6.294	-4.878	-5.714	-5.682
	[2.403]	[1.157]	[2.189]	[2.322]	[2.414]	[2.37]	[8.97]	[3.75]	[5.06]	[1.108]
Non-Intimate Homicide Rate	0.009	0	0.003	0.002	0.002	0.021	0.012	0.013	0.005	0.005
	[0.002]	[0.002]	[0.005]	[0.006]	[0.006]	[9.18]	[5.72]	[4.44]	[1.49]	[0.003]
Female population						0	0	0	0	0
						[9.73]	[9.45]	[4.08]	[0.40]	[0.000]
Shelters for victims of DV	-0.043	0.133	-0.017	-0.013	-0.034	0.002	0.116	0.024	0.053	0.048
	[0.052]	[0.028]	[0.047]	[0.047]	[0.052]	[0.04]	[2.55]	[0.52]	[1.28]	[0.040]
White	-2.056	-0.543	-1.671	-1.477	-1.466	-0.303	1.111	0.204	0.503	0.508
	[0.170]	[0.110]	[0.171]	[0.241]	[0.239]	[1.76]	[8.28]	[1.13]	[3.00]	[0.170]
Hispanic	-1.689	-0.625	-0.989	-0.827	-0.822	-0.471	0.534	0.305	0.566	0.568
	[0.112]	[0.070]	[0.115]	[0.227]	[0.226]	[3.97]	[6.13]	[3.15]	[6.18]	[0.092]
Ln(female population)	1.226	1.182	1.129	1.012	1.01					
	[0.072]	[0.045]	[0.084]	[0.185]	[0.184]					
Ln(female assaults)				0.095	0.092					
				[0.109]	[0.109]					
Female assaults									0.01	0.01
									[6.25]	[0.002]
Mandatory arrest policy					-0.094					-0.027
					[0.101]					[0.061]
Observations	198	198	191	191	191	198	198	198	198	198
R-squared	0.89	0.98	0.61	0.61	0.62					
Robust standard errors in brackets										
Interpretation						-3.1%	-4.0%	24.6%	14.5%	16.2%
Without LA or San Diego	Ln(female assaults)	Ln(car crashes)	Ln(arrests)	Ln(arrests)	Ln(arrests)	Female assaults	Car crashes	Arrests for Domestic Violence	Arrests for Domestic Violence	Arrests for Domestic Violence
No drop policy	-0.044	0.096	0.25	0.253	0.244	0.045	0.052	0.292	0.209	0.163
	[0.109]	[0.048]	[0.076]	[0.078]	[0.073]	[0.087]	[0.042]	[0.055]	[0.055]	[0.055]
Observations	165	165	158	158	158	165	165	165	165	165
R-squared	0.86	0.96	0.49	0.49	0.49					
Robust standard errors in brackets										
Interpretation						4.6%	5.3%	33.9%	23.2%	17.7%
County fixed effects and a quadratic time trend included in all regressions										

Figure 3A:
Intimate Homicid Victims by Sex:
1979-1996 National

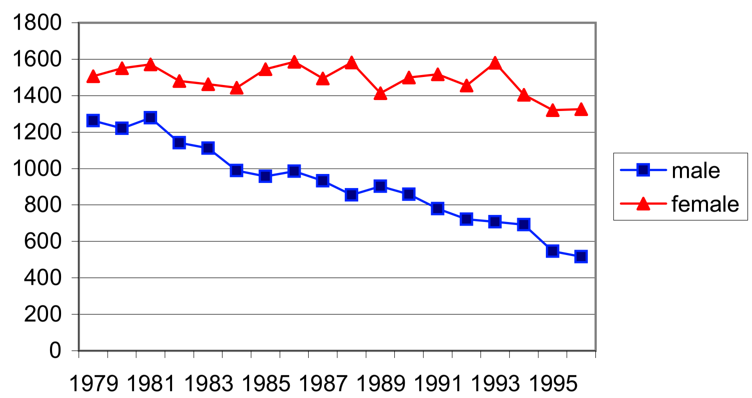

Figure 4: Average number of homicides per city before and after no-drop

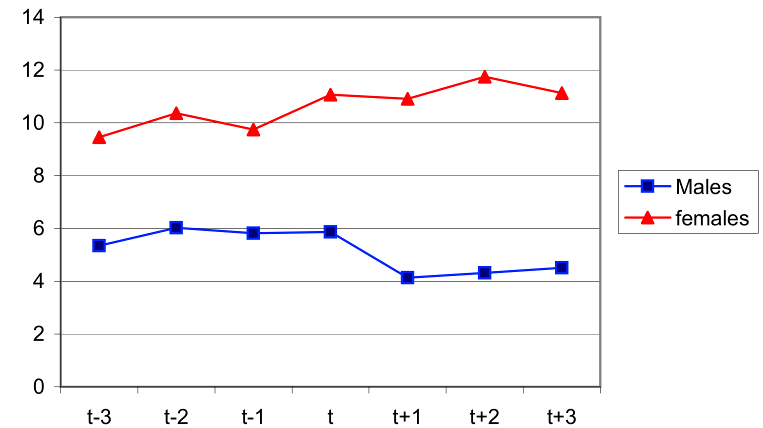

Figure 3B:
Intimate Homicide Victims by Sex:
1979-1996 48 Cities

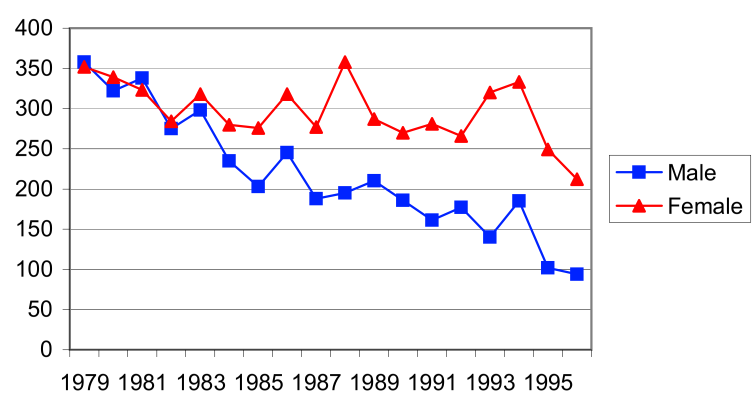

Figure 5: Impact of no-drop policies on arrests for domestic violence